CLAIMS

What is claimed is:

1. A system that facilitates learning Bayesian networks with local distributions, where at least one distribution is not a complete table, comprising:

a complete data set;

a Bayesian network constructor component that constructs a complete-table Bayesian network to represent local distributions of data in the complete data set and employs a learning algorithm that can reverse edges in the complete-table Bayesian network to facilitate learning a decision-tree Bayesian network.

2. The system of claim 1, the Bayesian network constructor component further analyses a directed acyclic graph that results from the complete-table Bayesian network to determine a partial ordering of the complete-table Bayesian network.

3. The system of claim 2, the learning algorithm permits construction of the local distributions to the partial ordering of the directed acyclic graph of the complete-table Bayesian network.

4. The system of claim 1, the Bayesian network constructor component determines a score for each edge in the complete-table Bayesian network.

5. The system of claim 4, the Bayesian network constructor component determines a score for at least one other potential edge configuration in the complete-table Bayesian network to assess whether the score of an edge can be improved.

6. The system of claim 5, the Bayesian network constructor component manipulates at least one edge in the complete-table Bayesian network if manipulation of the edge will improve the score of the edge.

7. The system of claim 6, the local distributions comprise at least one decision tree.

8. The system of claim 6, the local distributions comprise at least one support vector machine.

9. The method of claim 6, the local distributions comprise at least one logistic regression.

10. A method for learning Bayesian networks with at least one distribution that is not a complete table, comprising:

inputting a complete data set;

learning a first Bayesian network that comprises complete tables;

analyzing a directed acyclic graph of a complete-table Bayesian network; and

learning a second Bayesian network that comprises a distribution with at least one non-complete-table-distribution.

11. The method of claim 10, learning the first Bayesian network comprises employing a search algorithm that can reverse edges in the complete table Bayesian network.

12. The method of claim 11, further comprising determining a score for at least one edge in the complete-table Bayesian network.

13. The method of claim 12, further comprising determining scores for other potential edge configurations in the complete-table Bayesian network.

14. The method of claim 13, further comprising comparing the score of the the at least one edge to the score for another potential edge configuration to determine whether the score of the at least one edge can be improved.

15. The method of claim 14, further comprising refining the complete-table Bayesian network by manipulating the at least one edge to improve the score of the at least one edge if it is determined that the score of the at least one edge can be improved.

16. The method of claim 15, further comprising refraining from manipulating edges in the complete-table Bayesian network if it is determined that no edge score can be improved.

17. The method of claim 16, further comprising deriving a set of constraints on construction of the local distributions in the second Bayesian network based on the directed acyclic graph of the complete-table Bayesian network once it is determined that no edge score can be improved.

18. The method of claim 17, deriving the set of constraints comprises evaluating the directed acyclic graph of the complete-table Bayesian network to identify all edges in a refined complete-table Bayesian network.

19. The method of claim 18, learning the second Bayesian network comprises employing a constrained learning algorithm that respects the partial order of the directed acyclic graph of the refined complete-table Bayesian network.

20. The method of claim 19, further comprising growing decision trees as local distributions that define the second Bayesian network.

21. The method of claim 12, determining a score for at least one edge comprises:

determining a degree of dependency between nodes connected by the at least one edge;

determining a direction of dependence between nodes connected by the at least one edge; and

assessing whether the direction of that at least one edge is correct based at least in part on the direction of dependence between nodes connected by the at least one edge.

22. The method of claim 21, further comprising determining whether the score of the at least one edge is a best possible score by comparing the score of the at least one edge to scores for all other possible arrangements of the nodes and the at least one edge.

23. The method of claim 22, further comprising reversing the direction of the edge to improve edge score if the score of the at least one edge is lower than a score for another possible arrangement of the nodes and the at least one edge.

24. A data packet transmitted between two or more computer components that facilitates data access, the data packet comprising data set information, based, in part, on a complete data table-based model or pattern.

25. The data packet of claim 24, the data packet further comprising data set information based directly from the data set.

26. The data packet of claim 25, the data packet further comprising data set information based on a complete data table.

27. A data packet transmitted between two or more computer components that facilitates data access, the data packet comprising data set information useable for learning a Bayesian network with decision trees, based, in part, on a Bayesian network with complete data tables.

28. A device employing the system of claim 1 comprising at least one of a computer, a server, and a handheld electronic device.

29. A system that facilitates learning Bayesian networks with decision trees, comprising:

means for learning a complete-table Bayesian network from a data set;

means for refining a directed acyclic graph resulting from the complete-table Bayesian network; and

means for learning a Bayesian network with at least one non-complete-table distribution, whereby local distributions are constructed in accordance with constraints imposed by a partial order of the directed acyclic graph of the complete-table Bayesian net.